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Authors
Sánchez, José J
Baerenklau, Kenneth

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José J. Sánchez (Corresponding author)
Research Economist
USDA Forest Service
Pacific Southwest Research Station
4955 Canyon Crest Drive
Riverside, CA. 92507, U.S.A.
jose.sanchez2@usda.gov
(951) 680-1560

Kenneth Baerenklau
Associate Professor of Environmental Economics and Policy
University of California, Riverside
Riverside, CA. 92521, U.S.A.
ken.baerenklau@ucr.edu
(951) 827-2628

Armando González-Cabán
Research Economist
USDA Forest Service
Pacific Southwest Research Station
4955 Canyon Crest Drive
Riverside, CA. 92507, U.S.A.
armando.gonzalezcaban@usda.gov
(951) 680-1525

How Sensitive are Spatial Estimates of Wilderness Recreation Values to Information about Hiking Destinations?

Abstract

This study uses individual survey data to investigate the impact of information about hiking destinations on estimated wilderness values in a spatial context. The data is derived from a revealed preference survey of backcountry visitors who responded to questions about their recreation behavior in the San Jacinto Wilderness of southern California. Two GIS data layers are developed showing spatial representations of non-market values derived from a Kuhn-Tucker demand model, with and without destination information. Each pixel in each data layer contains an estimate of the recreation value at that location. The destination data provides more detailed information on recreation behavior that can be used to more accurately allocate the landscape values. Results show that including destination information produces significantly greater heterogeneity in parcel value estimates for large areas of the wilderness.

Keywords: GIS, Kuhn-Tucker demand system model, Nonmarket valuation, Web-based survey, Viewshed analysis

1. Introduction

Given limited budgets, the need for economic valuation of public land has become vital for maintaining public access and conservation of our nation's public lands. The use of spatial analysis software benefits forest management because it provides a better spatial representation of forest lands and helps the decision making process. The use of this software is now possible because recent increases in computing power have given researchers the ability to make greater use of geographic information systems (GIS). As use of this tool has increased, researchers have begun combining GIS software with non-market valuation methods to assist land and forest managers (Baerenklau et al., 2010; González-Cabán et al., 2003). This combination has allowed researchers to derive spatially-explicit representations of landscape values.

Non-market valuation methods such as travel cost analysis, contingent valuation, and hedonic pricing have been used to help inform management decisions. Mapping of ecosystem services values has been increasing in the past several years as seen by the number of cases reported in Crossman et al. (2013), Schägner et al. (2013), and Wolff et al. (2015). GIS in conjunction with non-market valuation methods has been used to derive spatially explicit landscape values. For example, Eade and Moran (1996) developed an "economic value map" for the Rio Bravo Conservation Area in Belize using the benefit transfer method and GIS to spatially allocate ecosystem service values. Troy and Wilson (2006) used a similar approach to produce a map of ecosystem service flow values based on land cover types for three case studies. González-Cabán et al. (2003) estimated the effect of prescribed burning on deer harvest by using time-series data and GIS approaches with travel cost and contingent valuation methods. Additionally, Cavailhès et al. (2009) evaluated the landscape values of Dijon, France and found land cover around houses has an effect on housing prices using GIS and hedonic price model.

A highly relevant work for this study is the GIS-based landscape valuation application by Baerenklau et al. (2010). The authors use recreation permit data and a zonal travel cost method to estimate the aggregate recreation values. They then spatially allocate that value to the landscape using GIS-based "viewshed" analysis. Due to the absence of information about hiking routes or destinations, the authors assumed that when a hiker encountered a trail junction, s/he took each path with equal probability. However, the equal probability assumption underestimates the values of popular destinations and related parts of the landscape because in reality a trail junction leading to more visited destinations will have a higher probability than less frequently visited destinations. The extent to which spatial wilderness valuations are affected by incomplete information about spatial patterns of site use is the main subject of this paper.

To-date there is a paucity of publications in this subject area. A study by Paracchini et al. (2014) uses population distribution and behavior datasets to map and assesses outdoor recreation opportunities for the European Union at a continental scale but does not include an economic valuation of recreation opportunities nor a spatial allocation over the landscape. Chiou et al.

(2010) found optimal travel routes based on time and energy cost consumption to inform managers and visitors of trail difficulty. However, the authors do not derive recreation values. Another study by Ji et al. (2016) found that using the “nearest access point” approach to model recreation demand with incomplete information about where people actually access a large geographic site can lead to biased travel cost estimates. Schägner et al. (2016) map estimated recreational values for European National Parks using predicted annual visits with monetary value estimates. However the authors use the “value transfer” method and assume a constant value per visit. To the best of our knowledge, ours is the first study that uses information about routes utilized on-site to estimate wilderness recreation values in a spatial context. To do this, we use a web-based survey to elicit information on hiking entry points and destinations visited over a season to develop individual hiking routes. This information is missing in Baerenklau et al. (2010) and is potentially useful to more rigorously allocate the wilderness recreation value across the landscape.

This study contributes to the recreation demand literature by advancing the standard methodology for environmental valuation which focuses on valuing access to what is often a spatially expansive resource as a singular good and potentially helps to refine our understanding of environmental values associated with preserved areas. In addition, we address the question of whether the additional cost and effort of collecting route and destination information has policy-relevant implications for demand and welfare analysis. Our results also can help researchers and managers better understand and address the economic effects of natural or human-made disaster that damage or impact natural resources in location-specific ways. Examples include management of wildfire, pest infestation, resource extraction, pollution, and land development pressures on open space.

2. Study Area and Data[1]

This study investigates backcountry hikers who visit the San Jacinto Wilderness, San Bernardino National Forest in southern California (figure 1). The wilderness is located within a 2.5 hour drive from the highly urbanized Los Angeles, Orange, Riverside, San Bernardino, and San Diego counties. It covers 13,350 hectares with elevations ranging from 1,800 to 3,300 meters.

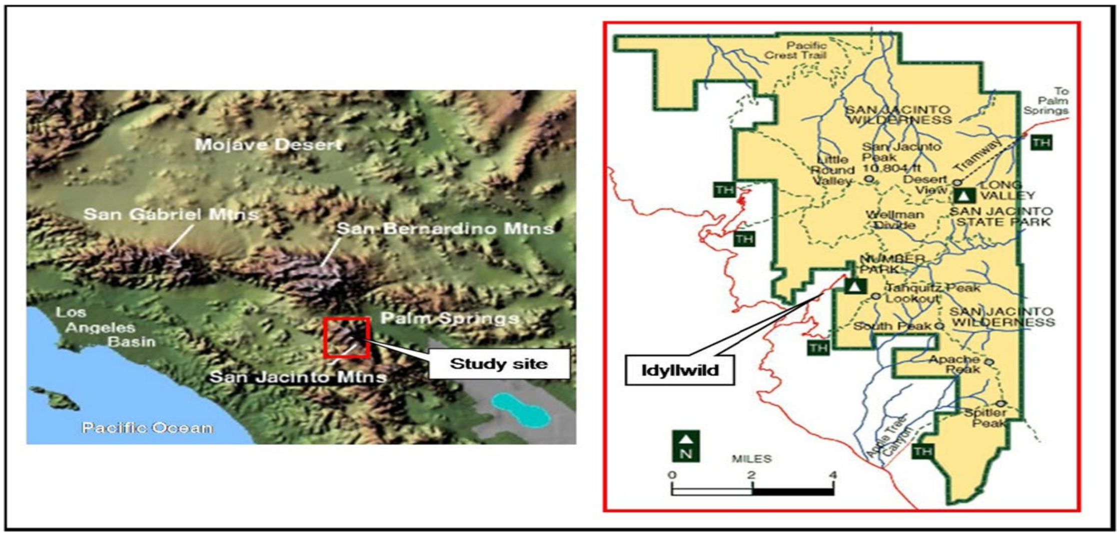

Figure 1— Site location-San Jacinto Wilderness area. Map provided by Baerenklau et al. (2010).

The most popular recreation activity is day hiking (Baerenklau et al. 2010). There was a total of 55,239 visitors (table 1) who obtained backcountry permits to enter the wilderness area during 2011 (Andrew Smith and Bart Grant, personal communication, USDA Forest Service and Mt. San Jacinto State Park Ranger, October 2013).

Table 1 *—Total San Jacinto wilderness visitors (2011) to selected trails and destinations*

Trailhead	Visitors	Destination	Visitors[2]
Deer Springs	6,271	San Jacinto Peak	9,297
Devil's Slide	12,362	Round Valley	6,862
Marion Mtn	2,325	Round Valley Loop	6,346

[1] See Sánchez et al. (2016) for a complete survey design and data collection procedure.
[2] Source: Bart Grant, personal communication, Mt San Jacinto State Park Ranger, October 2013. Destination visitor total is less than trailhead visitor total because the California State Parks collects destination information for the Long Valley trailhead only.

South Ridge	2,118	Hidden Valley	280
Long Valley	32,163	Tamarack	257
Total	55,239	Total	23,042

This study uses a web-based survey to collect revealed preference data from backcountry visitors during the summer months of June 2012 to September 2012. Recreationists visiting the Idyllwild and Long Valley Ranger Stations were asked to participate in an online survey. To help increase response rates, undergraduate students were stationed at both ranger stations to provide the study description, incentives for participating in the survey, and collecting email addresses of potential survey participants. The online survey was implemented using a modified Dillman et al. (2014) approach. Those agreeing to participate received an email invitation within a week of their wilderness visit with a link to the online survey. Approximately one week after receiving the survey link, non-responders received an e-mail reminder to complete the survey. A final e-mail reminder was sent to non-responders approximately 3 weeks after the initial contact. Out of 1527 invitations sent, a total of 698 usable surveys were collected, for an effective response rate of 46%. The survey collected socio-demographics (e.g., age, education level, gender, income, race, home zip code, and whether the respondent is currently a member of an environmental conservation organization) and recreational information (e.g., number of trips to each trailhead, number of trips to each destination). The travel cost for each individual trip was estimated to be the sum of driving and time costs. Driving costs are a function of distance (using Google Maps) and the average per-mile cost of operating a typical car ($0.585/mile; AAA, 2012). Time costs are a function of travel time (also from Google Maps) and the opportunity cost of time was included as one-third of respondent’s average hourly income (Hagerty and Moeltner, 2005). For trips originating on the east side of the wilderness and entering through Long Valley (see figure

1), the cost of riding the Palm Springs Aerial Tramway into the state park was also included in the trip cost.

3. Estimation of forest recreation values

Benefits of landscape conservation are derived from revealed preference data using a Kuhn-Tucker (KT) demand system (Phaneuf et al., 2000; von Haefen et al., 2004). The KT demand model is one of the most recently developed approaches for analyzing seasonal, multi-site recreation demand data. One advantage over other multiple site recreation demand models (e.g., count data models) is that it can model simultaneous decisions, the number of site visits and how many trips to each site during the year, using a single utility maximization framework. The KT model also accounts for corner solutions or zero visitations, which can be a significant portion of recreation data. In addition to having these advantages, it appears that similar policy inferences can be found between KT models and other recreation demand models. For example, von Haefen and Phaneuf (2003) compared the KT model and count data demand system model using Iowa wetlands recreation survey data and found a general convergence of welfare estimates. While Herriges et al. (1999) found that the KT model outperforms the linked model for angling in the Wisconsin Great Lakes region. However, despite the advantages over traditional models, the KT models have not been used that often in recreation demand. See Sánchez et al. (2016) and Nicita et al. (2015) for recent recreation demand application of the KT model.

In a KT demand model, the individual's direct utility function is $u(x, z; q, \varepsilon, \Gamma)$, where x is a vector of trips taken to each trailhead j, z is spending on all other goods with price normalized to one, q is a vector of site characteristics, ε is random error term unknown to the researcher, and Γ represents parameters of the utility function to be estimated. Individuals maximize utility over a season subject to their budget constraint:

$$(1) \quad \max_{x,z} u(x, z; q, \varepsilon, \Gamma), \qquad s.t. \;\; y = z + xp, \quad x_j \geq 0, j = 1, \dots, M,$$

where y is the annual income and p is the price (travel cost) of visiting each trailhead access point. The first-order conditions that implicitly define the solution to the optimal consumption bundle (x^*, z^*) are

$$(2) \quad \frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} \leq p_j, j = 1, \dots, M,$$

$$(3) \quad x_j \times \left[\frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} - p_j \right] = 0, j = 1, \dots, M.$$

Following von Haefen et al. (2004), the specific parameterization we use for the utility function is the following[3]:

$$(4) \quad U = \sum_{j=1}^{M} \Psi_j \, ln\left(\phi_j x_j + \theta\right) + \frac{1}{\rho} \, z^{\rho},$$

$$\Psi_j = exp\left(\delta' s + \varepsilon_j\right) \qquad j = 1, \dots, M$$

$$\phi_j = exp\left(\gamma' q_j\right)$$

$$\rho = 1 - exp(\rho^*)$$

$$\mu = exp(\mu^*)$$

$$\theta = exp(\theta^*)$$

$$z = y - p' x$$

$$\varepsilon_j \sim EV(\mu)$$

[3] This was first suggested by Bockstael et al. (1986) and later modified by von Haefen et al. (2004).

where **s** is a vector of individual characteristics, z is spending on all other goods (a function of travel cost and income), $\varepsilon_1, \ldots, \varepsilon_M$ represent unobserved heterogeneity, and $\delta, \gamma, \theta^*, \rho^*,$ and μ^* are structural parameters. There are some features of the utility function that warrant further discussion. The KT model assumes additive separability, which implies weak substitution effect for goods with small income effects. This assumption may lead to overestimation of welfare losses due to individual site closures (Kuriyama and Hanemann, 2006). The KT specification also guarantees that weak complementarity is satisfied for all parameter values (von Haefen et al., 2004), implying that all values derived from the quality attributes of a good arise through its use (von Haefen, 2007).

Rearranging equations 2 and 3 (Phaneuf et al., 2000) and using the utility function in equation 4, the implicit equation for ε can be solved using the KT conditions, yielding the following first-order conditions:

$$(5) \quad \varepsilon_j \leq g_j(x, y, p; q, \gamma),$$

$$x_j \geq 0, \qquad x_j\left[\varepsilon_j - g_j(x, y, p; q, \gamma)\right] = 0$$

where $g_j(x, y, p; q, \gamma)$ is the solution to $\left[\frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} - p_j\right] = 0$. If we assume the ε_j are independent and each follows a type I extreme value distribution, then we can use equation 5 to derive the probability of observing an individual's trip-taking outcome. The probability that x trips are taken is $prob\left(x_j = x\right) = prob\left(\varepsilon_j = g_j\right)$ (Phaneuf and Siderelis, 2003). Therefore, the likelihood of observing an individual's outcome x conditional on the structural parameters, $(\delta, \gamma, \theta^*, \rho^*, \mu^*)$, is (von Haefen et al., 2004; von Haefen and Phaneuf, 2005):

$$(6) \quad L(x|\delta, \gamma, \theta^*, \rho^*, \mu^*) = |\mathbf{J}| \prod_j \left[exp\left(-g_j(\cdot)/\mu\right)/\mu\right]^{1_{x_j>0}} \times \; exp\left[-exp\left(-g_j(\cdot)/\mu\right)\right],$$

where $|\mathbf{J}|$ is the determinant of the Jacobian for the transformation from ε to (x_j, ε_j) and $1_{x_j>0}$ is an indicator function equal to one if x_j is strictly positive and zero otherwise. We used a conventional maximum likelihood method for estimating the fixed parameter model and a maximum simulated likelihood method for estimating the random parameter model (Gourieroux and Monfort, 1996).

Welfare estimation is possible in the KT framework using Hicksian consumer surplus (CS^H), but no close-form solution exists. Therefore, computation of the welfare estimates must be done using Monte Carlo simulation techniques. The iterative algorithm of von Haefen et al. (2004) estimates CS^H using an efficient numerical bisection routine. Details on the procedure can be found in von Haefen et al. (2004) and von Haefen and Phaneuf (2005).

3.1 Estimation Results[4]

For the present investigation, parameter estimates are derived for two separate analyses, each using the same dataset: (1) revealed preference estimates using trailhead entry points as sites and (2) revealed preference estimates using trailhead/destination pairs as sites. The two analyses use the same information on visitors (n=698) and the same total number of trips (n=3840), but differ in the number of sites in the model. The first analysis uses 5 sites: one for each of the 5 trailheads examined in the survey. There are more trailheads in the San Jacinto Wilderness, but only 5 sites were selected because 97% of all visits are taken to these 5 trailheads[5]. We assume negligible recollection bias due to the typically small number of annual

[4] The parameter and welfare estimate were derived using Matlab (MathWorks, 2015) code generously provided by Dan Phaneuf.
[5] Out of a total of 34,218 permitted visitors to the San Jacinto Wilderness, 33,194 visited the 5 trails (Baerenklau et al. 2010). Similar results were found using 2011 wilderness permit data.

trips per person taken to the wilderness (table 2). In order to spatially allocate access value in this model, we invoke the "equal probability" assumption as in Baerenklau et al. (2010).

Table 2*—Summary statistics for trips per person to trailheads and trailhead/destination routes*

Trail name	Mean (std. dev.)	Min/Max
Deer Springs trailhead	0.11 (0.46)	0/5
Devil's Slide trailhead	1.86 (6.95)	0/116
Marion Mtn trailhead	0.21 (0.74)	0/8
South Ridge trailhead	0.36(1.18)	0/16
Long Valley trailhead	2.97 (7.97)	0/100
Deer to San Jacinto Peak route	0.07 (0.36)	0/5
Deer to Saddle Junction route	0.03 (0.28)	0/5
Devil's to San Jacinto Peak route	0.05 (0.30)	0/4
Devil's to Saddle Junction route	0.89 (3.07)	0/51
Devil's to Tahquitz Valley route	0.21 (1.24)	0/20
Devil's to Skunk Cabbage route	0.41 (2.13)	0/38
Devil's to Tahquitz Peak route	0.22 (0.85)	0/13
Devil's to Round Valley route	0.05(0.37)	0/7
Devil's to Hidden Valley route	0.03 (0.43)	0/10
Marion Mtn to San Jacinto Peak route	0.11 (0.43)	0/4
Marion Mtn to Little RV route	0.09 (0.37)	0/4
S. Ridge to Saddle Junction route	0.06 (0.30)	0/4
S. Ridge to Tahquitz Valley route	0.08 (0.36)	0/4
S. Ridge to Skunk Cabbage route	0.06 (0.30)	0/4
S. Ridge to Tahquitz Peak route	0.16 (0.54)	0/6
Long Valley to San Jacinto Peak route	0.57 (1.64)	0/28
Long Valley to Little RV route	0.51 (2.77)	0/51
Long Valley to Tamarack route	0.34 (1.74)	0/33
Long Valley to Hidden Valley route	0.33 (1.62)	0/33
Long Valley to Round Valley route	1.23 (3.36)	0/33

n = 698

In the second analysis, sites are redefined as trailhead-destination pairs based on additional information reported in the survey. To determine hiking routes, we first identified more than 40 possible trailhead-destination routes using the trail network. We then omitted routes deemed too long for a day hike (typically more than 16 miles round-trip) and those that did not start and end at the same trailhead. We then made further refinements based on information obtained from the Idyllwild station Ranger[6]. Ultimately a total of 20 allowable hiking routes (sites) remained.

To implement the model and capture individual preferences for site characteristics, we need both individual (Ψ matrix) and site characteristics (Φ matrix) information. Lacking site characteristics data, the site-specific (trailhead) dummy variables were used in the Φ matrix. Each dummy variable captures the combined effect of multiple (unobserved) attributes on the desirability of visiting a particular trailhead.[7] Using the dummy variables in the Φ matrix is appropriate because these variables account for the distinct features of each site: elevation gain, vegetation (chaparral at lower elevations and Yellow and Ponderosa pine at higher elevations), panoramic views, trail distance and hiking difficulty for which we have only anecdotal information. For example, Long Valley trailhead has no chaparral vegetation and its lowest elevation is over 2,590 meters. The other trailheads (Deer Springs, Devil's Slide, Marion Mountain, and South Ridge) have lower elevations, ranging from 1,707 to 2,073 meters and consist of chaparral vegetation near the beginning of the trail. As elevation increases, vegetation changes to pine.

Table 3 shows the estimation results for the trailhead-only model.[8] The Ψ matrix (individual characteristics) shows that being male, older, employed full-time, and belonging to an environmental group increases trip frequency to each trailhead. The remaining parameters on minority status and having at least a bachelor's degree are not statistically significant. The Φ

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[6] The Idyllwild District Ranger provided a list of highly unlikely hiking routes for an average recreationist, given the difficulty, trail distance, and better alternative trail that leads to the same destination.

[7] For identification purposes, the Deer Springs trailhead was removed from the trailhead-only model and Deer Springs to San Jacinto Peak hiking route was removed from the trailhead-destination model.

[8] These results differ from Sánchez et al. (2016) because here we have trimmed the dataset to create a common set of trips that can be used across both models.

parameter estimates demonstrate the popularity of the trails and have magnitudes that are consistent with the visitation data shown in tables 1 and 2.

Table 3— *Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead (trailhead-only model).*

Parameter	**Model**		
	Estimate	**Std. Err.**	**t-statistics**
Ψ Index parameters			
Constant	-10.0277**	1.8890	-5.3084
Gender	0.8884***	0.1549	5.7352
Age	0.0215***	0.0083	2.6013
EnvGrp	0.6330***	0.1215	5.2083
Minority	0.2012	0.2744	0.7334
Degree	-0.1396	0.1827	-0.7640
Employed	0.4589***	0.1507	3.0459
Translating parameter			
Θ	1.1953	62.4608	0.0191
Φ *parameters*			
Constant	-1.1953	62.4609	-0.0191
Devil’s Slide Dummy	1.1553***	0.0899	12.8507
Marion Mtn Dummy	0.5123***	0.1005	5.0976
S. Ridge Dummy	0.6924	0.0953	7.2695
Long Valley Dummy	1.5089***	0.0900	16.7747
Rho parameter			
ρ	-0.0050	0.1701	-0.0295
Type I extreme value scale parameter			
μ	-0.3746***	.00380	-9.8539
Log-likelihood	-3313.38		

Note: *** indicates significance difference from zero at the 0.01 level. Robust standard errors reported.

Table 4 contains estimates for the trailhead/destination model. The results for the Ψ parameters show that being male, belonging to an environmental group, and having at least a bachelor’s degree increases visitation to each hiking route. The other parameters on age, minority status and full-time employment are statistically insignificant. For the Φ parameters, we find the largest magnitudes are associated with all of the Long Valley and Marion Mountain hiking routes, five of the Devil’s Slide routes, and two of the South Ridge routes. This is consistent with the popularity of the routes as shown in tables 1 and 2, as well as the observation that hiking from Deer Springs to Saddle Junction, and Deer Springs or Devil’s Slide to San Jacinto Peak, is extremely difficult for the average recreationist due to steepness and distance (approximately 9.2, 8.2, and 8.0 miles one-way trip, respectively).

Table 4— *Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each hiking route (trailhead/destination model).*

Parameter	**Model**		
	Estimate	**Std. Err.**	**t-statistics**
Ψ Index parameters			
Constant	-2.2582***	0.4951	-4.5610
Gender	0.5072***	0.0581	8.7249
Age	-0.0019	0.0026	-0.7354
EnvGrp	0.3067***	0.0594	5.1613
Minority	0.1032	0.0994	1.0382
Degree	0.1465**	0.0678	2.1604
Employed	0.0777	0.0634	1.2266
Translating parameter			
Θ	0.8306	73.9016	0.0112
Φ parameters			
Constant	-0.8306	73.9012	-0.0112
Deer to Saddle Junction	-0.7083***	0.1945	-3.6424
Devil's to San Jacinto Peak	-0.1508	0.1771	-0.8515
Devil's to Saddle Junction	1.5629***	0.1233	12.6802
Devil's to Tahquitz Valley	0.6799***	0.1376	4.9411
Devil's to Skunk Cabbage	1.0512***	0.1306	8.0484
Devil's to Tahquitz Peak	0.7929***	0.1337	5.9305
Devil's to Round Valley	-0.2341	0.1836	-1.2753
Devil's to Hidden Valley	-1.2338***	0.2901	-4.2524
Marion Mtn to San Jacinto Peak	0.7006***	0.1390	5.0415
Marion Mtn to Little RV	0.6285***	0.1420	4.4246
S. Ridge to Saddle Junction	0.1494	0.1606	0.9307
S. Ridge to Tahquitz Valley	0.4114***	0.1490	2.7605
S. Ridge to Skunk Cabbage	0.1217	0.1621	0.7505
S. Ridge to Tahquitz Peak	0.8694***	0.1338	6.4981
Long Valley to San Jacinto Peak	1.8349***	0.1226	14.9706
Long Valley to Little RV	1.3237***	0.1313	10.0798
Long Valley to Tamarack	1.1042***	0.1364	8.0949
Long Valley to Hidden Valley	1.0819***	0.1375	7.8689
Long Valley to Round Valley	1.8882***	0.1235	15.2864
Rho parameter			
ρ	-.9237***	.1158	-7.9737
Type I extreme value scale parameter			
μ	-0.1408***	.0219	-6.4251
Log-likelihood	-7564.17		

Note: ** and *** indicates significance difference from zero at the 0.05 and 0.01 levels respectively. Robust standard errors reported.

Overall these models exhibit both intuitive similarities as well as some differences, and demonstrate the effect that site definitions can have on model estimation results. We also analyzed alternative model structures, including several KT random parameter specifications. However, the mean and dispersion parameters were not statistically different from zero. We followed Nicita et al. (2015) to compare random and fixed coefficient models using the consistent Akaike Information Criteria (Bozdogan, 1987). Based on the results, we only report the fixed coefficient model here because this specification has a better fit to the data. Other results are available from the authors upon request.

3.2 Welfare Analysis

We use the numerical bisection method developed by von Haefen et al. (2004) to derive recreation value estimates for the sites in each model[9]. This iterative algorithm produces Hicksian consumer surplus to find the income compensation that equates utility before and after a price and/or quality change. The trailhead-only analysis uses the parameter estimates from table 3 to simulate the welfare loss that might be associated with a high intensity wildfire or other disturbance that would result in closure of one or more sites. Therefore, the welfare loss is the foregone value of recreation if access to the site is restricted (e.g., a trailhead closure). To account for uncertainty in the parameter estimates as well as nonlinearities in the welfare calculation, we take 500 random draws from the estimated parameter distributions to simulate distributions for the welfare losses.

Table 5 reports the average simulated welfare losses for the trailhead-only model, along with the standard errors. The table shows that the individual mean welfare loss is the greatest for Long Valley and Devil's Slide, with Deer Springs being the site with the lowest welfare loss. This reflects both the popularity of the sites as well as differences in travel costs to access each site, as there is the additional cost of riding the Palm Springs Aerial Tramway to access the Long Valley site. Standard errors are relatively small.

[9] Note that we do not extrapolate these estimates to the entire population of potential users. This is because the present study is motivated by a methodological question rather than an interest in the aggregate value of the study site to the broader population. Therefore we do not concern ourselves with establishing the representativeness of our sample for the broader population.

__Table 5__— Mean individual seasonal welfare loss due to trailhead closure (2012 dollars).

Scenario	Mean	Std. Err.
Loss of Deer Springs site	-$6.18	0.3885
Loss of Devil's Slide site	-$146.40	5.6315
Loss of Marion Mtn site	-$17.74	0.8728
Loss of South Ridge site	-$26.22	1.2099
Loss of Long Valley site	-$313.90	11.2372
Loss of All sites	-$515.78	19.1941

Note: Mean seasonal welfare estimates based on 500 random draws from the parameter distributions (trailhead-only model, table 3).

We use the same procedure for the trailhead/destination model, but using table 4 to draw the random coefficients. This analysis, presented in table 6, shows that the highest welfare losses again are for the Long Valley and Devil's Slide routes, and the lowest for Deer Springs. Standard errors are again relatively small. Table 6 also shows that when we aggregate these route-specific values into trailhead values, we derive estimates very similar to those in table 5, with differences ranging from 2-7%. However none of these differences are statistically significant at standard significance levels.

__Table 6__ — Mean seasonal individual welfare estimate for selected trailhead/destination hiking route (2012 dollars).

Scenario	Mean	Std. Err.	Aggregate Mean Value
Loss of Deer Springs & San Jacinto Peak route	-$4.77	0.2528	
Loss of Deer Springs & Saddle Junction route	-$1.56	0.1119	
Loss of Deer Springs site	------	------	-$6.33
Loss of Devil's & San Jacinto Peak route	-$3.72	0.2029	
Loss of Devil's & Saddle Junction route	-$70.24	2.6880	
Loss of Devil's & Tahquitz Valley route	-$14.23	0.6325	
Loss of Devil's & Skunk Cabbage route	-$27.11	1.1018	
Loss of Devil's & Tahquitz Peak route	-$16.48	0.7368	
Loss of Devil's & RV route	-$3.30	0.1765	
Loss of Devil's & Hidden Valley route	-$2.14	0.1285	
Loss of Devil's Slide site	------	-----	-$137.23
Loss of Marion Mtn & San Jacinto Peak route	-$10.27	0.4841	
Loss of Marion Mtn & Little RV route	-$7.84	0.3791	
Loss of Marion Mtn site	------	-----	-$18.10
Loss of S. Ridge & Saddle Junction route	-$3.97	0.2118	
Loss of S. Ridge & Tahquitz Valley route	-$5.39	0.2709	
Loss of S. Ridge & Skunk Cabbage route	-$3.58	0.1946	
Loss of S. Ridge & Tahquitz Peak route	-$11.87	0.5445	

Loss of S. Ridge site	-----	-----	-$24.81
Loss of Long Valley & San Jacinto Peak route	-$59.76	2.3181	
Loss of Long Valley & Little RV route	-$47.56	1.7753	
Loss of Long Valley & Tamarack route	-$30.15	1.2124	
Loss of Long Valley & Hidden Valley route	-$28.76	1.1465	
Loss of Long Valley & Round V route	-$124.99	4.4763	
Loss of Long Valley site	-----	------	-$291.21
Loss of All routes	-$487.63	18.8815	

Note: Mean seasonal welfare estimates based on 500 random draws from the parameter distributions (trailhead/destination model, table 4).

4. Spatial Allocation Procedure

The estimation results in the preceding section show that introducing route and destination information in a site visitation model does not statistically change estimated site access values, but our main focus is on spatial representations of access value rather than just the site access values themselves. Our expectation is that there may be significant differences in spatially-explicit values across models. This is because, as demonstrated by Baerenklau et al. (2010), there already is heterogeneity in parcel-level landscape values associated with recreation activity from any particular access point. Introducing route and destination information is likely to increase this heterogeneity at the parcel level due to recreationists' tendency to seek out particular features within a landscape (e.g. streams, meadows, peaks, overlooks, well maintained trails, etc.), thus potentially creating policy-relevant value differences across models. Furthermore, the additional information should produce a more accurate representation of which parts of the landscape contribute most (and least) to recreationists' experiences, which also is of interest to resource managers.

The access or trip values estimated with the KT model (tables 5 and 6) can be allocated using the GIS-based viewshed tool to the individual parcels that together represent the landscape of our study to derive a recreation value map. We developed three such maps: (1) trailheads as sites; (2) trailhead/destination combinations as sites; and (3) the difference between maps 1 and

2. The trailhead approach follows the same method as Baerenklau et al. (2010) but uses individual rather than zonal recreation data. The trailhead/destination approach requires modifying the procedure slightly to include hiking routes as well. The difference in parcel-level values between these maps demonstrates the extent to which the use of additional—and often unobserved—destination information changes the welfare estimates in a spatial context.

The first step is to define the hiking routes used by visitors in each of the models. The web-based survey focused on 5 entry points: Long Valley and the 4 most popular entry points in Idyllwild. The survey data includes the entry point, sites and destinations visited, but the actual routes taken through the wilderness are unknown. Using GIS trail maps from the USDA Forest Service, the 20 most likely hiking routes were identified based on hiking distance, popularity of the destination and recommendations by the Forest Service Recreation Officer for the study area (Personal communication, October 2013). These trails consist of continuous segments that extend between two trail junctions or a junction and a destination.

The next step is to determine the likelihoods that each trail segment is used by a visitor. The method developed by Baerenklau et al. (2010) was implemented for the trailhead-only model. For this model, in the absence of any information about hiking paths, routes can be predicted by calculating the probability that a trail will be used during a one-day hiking trip. These calculations start at one of the 5 main entry points by assigning each entry trail an initial probability of 100% for a trip beginning at that trailhead. Trail segments leading away from trail junctions are then assigned equal probabilities. This means that if there is a two-way junction, the probability assigned to each trail segment leading away from this junction is 50%; the probability assigned to each segment leading away from a three-way junction is 33%, and so forth (see figure 2).

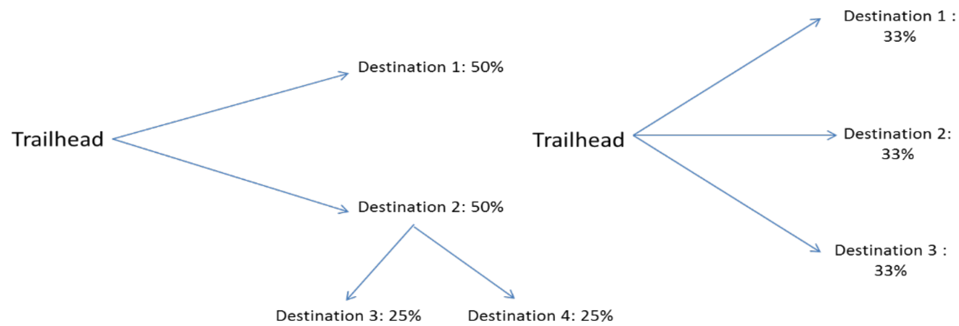

Figure 2- Probability tree assuming equal probability distribution

For the trailhead/destination model, the hiking routes were determined based on destinations visited and assumptions presented in section 3. The trail junction probabilities differ depending on access to destinations. For example, when arriving to a two-way junction, probabilities will be 1 if the trail segment leads to the desired destination and 0 if it leads to a different destination (see table 5 for hiking routes used in analysis).

The final step is to determine the monetary values for each trail segment and consequently for the entire landscape by establishing how the use of a trail implies value in the surrounding landscape. The allocation of trail values throughout the surrounding landscape is based on the concept of scenic quality. The recreation value of a parcel is a function of how frequently that parcel is viewed by visitors and from what distance it is viewed. Parcel values are higher when viewed often, and experienced at close range. The allocation of scenic quality value is based on the work by Higuchi (1983). The author defined a weighting function as a method for measuring the quality of visual landscape attributes based on their appearance from a specific observation point. Baerenklau et al. (2010) modified the suggested indices by increasing the distance to account for the vegetation type in their study area and increased the number of distance bands. We used the same approach as Baerenklau et al. (2010) to calculate recreational users' scenic value. The procedure uses a normalized weighting function that can be calculated for each point in the landscape, representing the scenic value for recreational users.

The visual experience of an individual hiker is simulated with a visibility analysis that was performed using the viewshed tool in ArcGIS[10] (ESRI, 2012). The viewshed tool identifies and calculates the number of times a location in a Digital Elevation Model (DEM) is visible by scanning the surrounding areas of one or more observations points. Locating areas of varying visual significance within the study site allows for a redistribution of the aggregate trip value across the heterogeneous landscape to allocate recreation values to individual parcels (30x30 meters). The values calculated for each parcel are then entered into the map layer.

4.1 Estimated Landscape Values

The mean welfare estimates shown in table 5 are used with the GIS-based viewshed tool to derive the landscape value map for the trailhead-only model. For all parcels, the annual values range from $0/ha to $19,466/ha throughout the wilderness, with a mean of $158.70/ha and standard deviation of $829/ha (figure 3). The high parcel values are concentrated in areas with high elevations (San Jacinto Peak) and popular sites (Long Valley). This is expected because our spatial allocation method is based on visibility; therefore parcels like these that are highly visible and/or frequently viewed received higher visibility weights and thus contribute more to the value of a trip. In contrast, parcels located in relatively remote areas and away from trails in our study have lower and sometimes no recreation value because of their limited visibility and/or low visitation rates (or having no data for a particular trailhead). However, this does not mean that those areas do not have economic value; rather we simply did not have any information to calculate the recreation values for those parcels.

[10] See Baerenklau et al. (2010) for viewshed tool settings used in the calculations.

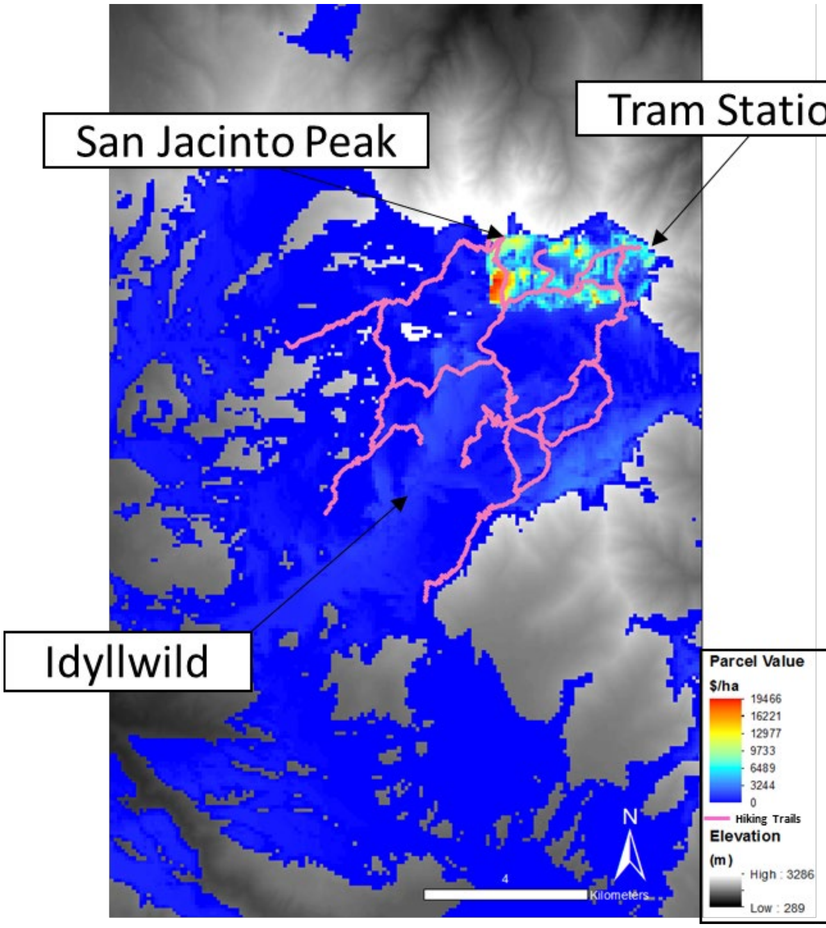

Figure 3 —Landscape values for trailhead-only model.

These parcel value estimates may be sensitive to the availability of destination information in the analysis. To investigate the magnitude of this sensitivity, we derive a similar map using the mean welfare estimates in table 6, which include information about specific hiking routes. Figure 4 shows the trailhead/destination landscape value map (same scale as figure 3). For all parcels, the annual values range from $0/ha to $18,866/ha throughout the wilderness, with a mean of $159.16/ha and standard deviation of $904/ha. As in the previous case, and for the same reasons, high parcel values are concentrated in higher elevations (San Jacinto Peak and Tahquitz Peak) and along popular hiking routes.

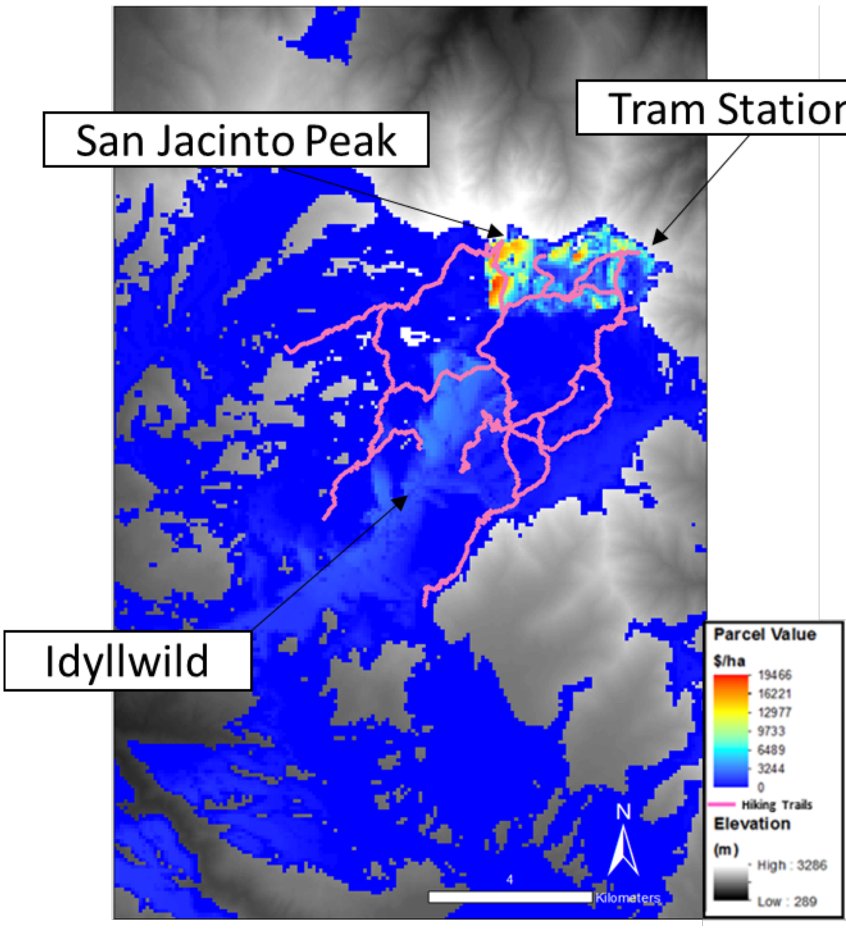

Figure 4— Landscape values for trailhead/destination model.

To assess if there are statistically significance differences between these two modeling approaches, we rely on the large sample properties of the two-sample t-test with unequal variances to test for equal means, and Levene's test (Levene 1960) to test for equal variances. The parcel value means are very similar in magnitude and are not statistically different (p-value = 0.78), however the variances are significantly different (p-value < 0.001). The first result reflects the fact that the welfare estimates for trailhead access also are not statistically different across models, while the second is consistent with our hypothesis that introducing destination information tends to increase parcel value heterogeneity across the landscape.

To further compare the magnitudes of the parcel-specific value estimates derived from these two models, we created a difference map in figure 5. This map was created by subtracting the trailhead/destination values map (figure 4) from the trailhead-only values map (figure 3). As shown in figure 5, the annual differences range from -\$9,538/ha to \$5,234/ha throughout the wilderness, with a mean of -\$0.46/ha. Assuming the trailhead/destination values are a better representation of the true values because they use available information about destinations, then the positive (negative) values in this map correspond to over- (under-) estimates by the trailhead-only model. Figure 5 shows that often, but not always, the trailhead-only model over- (under-) estimates generally lower (higher) parcel values. This pattern is consistent with the observed smaller variance of parcel values in the trailhead-only model. Moreover, these differences in parcel values are indicative of differences in spatial allocation methodologies across models, and imply that the “equal probability assumption” may not be a good approximation. It is apparent that this assumption tends to overvalue some areas, and undervalue others, likely because actual visitation is more concentrated on particular routes that lead to and have views of popular destinations and unique scenic elements of the landscape.

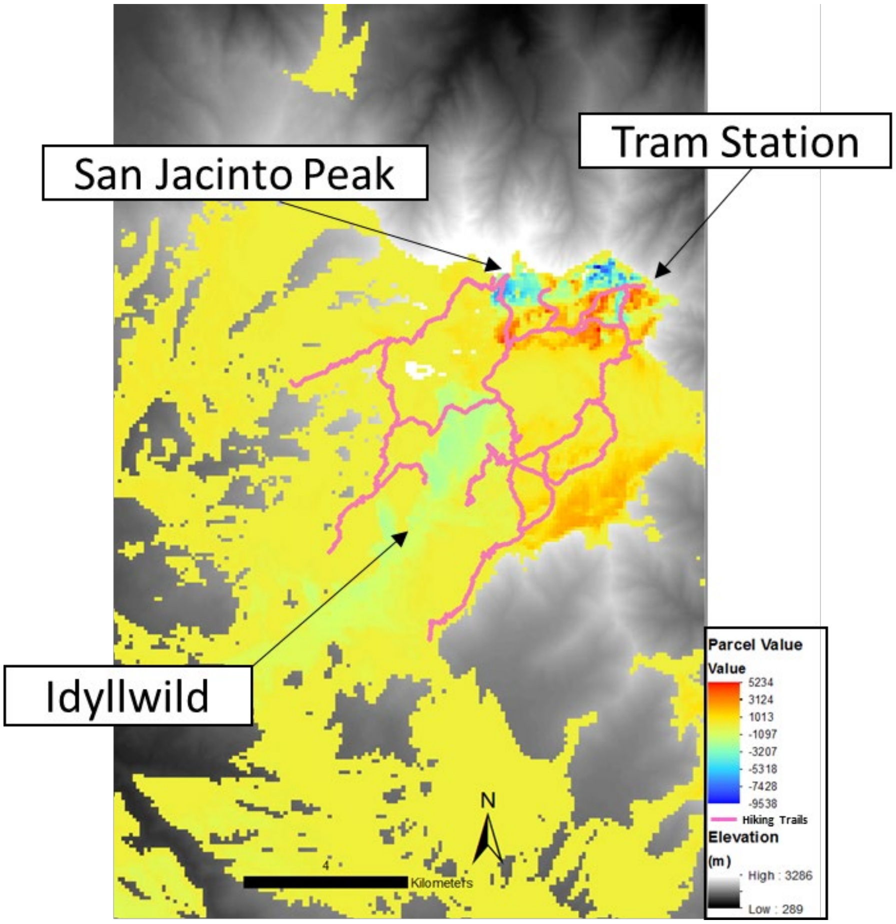

Figure 5—Over/under estimation by trailhead-only model.

5. Discussion and conclusion

Spatially explicit landscape values are potentially useful to forest managers because they provide a representation of the location-specific value of forestlands that can aid in making more effective land management decisions. Information from parcel value maps can be used to help manage risks to scenic quality from human or natural disturbances such as high intensity wildfires, pest infestations, invasive species, urban development, etc., assuming recreationists perceive these threats to the landscape as potentially degrading scenic quality. In addition, this information can potentially help forest managers with planning efforts including trail network design, campground development, siting/designation of scenic byways, and assessment of zoning regulations (such as building height limits).

This paper is the first to explore the implications of omitting wilderness destination information when deriving spatially explicit landscape values from a Kuhn-Tucker model of recreation demand. We hypothesize that omitting destination information and replacing it with assumptions about how visitors might traverse the wilderness will tend to smooth out parcel values too much, under-valuing popular areas and over-valuing less visited ones. Consistent with this hypothesis, we find that introducing route and destination information into the recreation demand model does not change the estimated access values significantly, but it does introduce noteworthy and statistically significant differences into the parcel value estimates. These differences – in some cases several thousands of dollars in value annually per hectare – are apparent both when comparing the variance of parcel values across models, and when viewing the associated parcel value maps. Therefore, we conclude that destination information is not as critical if the analyst only wants to estimate aggregate access value, but it is important for determining accurate parcel values due to the additional heterogeneity it introduces into parcel value estimates. Because this information typically can be obtained cheaply and easily when visitors must already register their wilderness trips through a permitting system, we believe that the destination-based analysis often would pass a benefit-cost test in practice.

One limitation of this approach (whether including destination information or not) is that the derived parcel value maps may show large areas with very low or zero value due to lack of information, or because the land cannot be seen from established access points within the landscape (such as trails). These blank areas should not be interpreted as having no value at all; rather they register no value given the available data and our scenic quality-based methodology for allocating recreation value. In such cases, additional valuation methods should be implemented to capture other types of land values and to ensure that parts of the landscape are not under-valued in the policy making process.

Another more technical limitation of this study is the weak substitution effects inherent in the Kuhn-Tucker model, which can overestimate the welfare losses due to individual site closures. This can potentially be a problem as we expect recreationists will most likely hike a different trail when encountering a trail closure, implying larger than estimated substitution effects. Future work should address this issue to better assess welfare losses due to simultaneous trail closures.

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